Can demand-driven training diminish labor turnover at worker and firm level?

The case of Brazil's Pronatec-MDIC

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Abstract

This paper explores for the first time the impact of a demand-driven training program on labor turnover at both worker and firm level. Launched in 2014 by the Ministry of Development, Industry and Trade (MDIC in Portuguese), Pronatec-MDIC allows firms to demand courses and nominate some of their workers. Difference-in-difference estimates finds that job tenure of workers that graduate from courses that their employers demand increases by 6 months. Labor turnover within demanding firms varies when considering different groups of workers who participate and did not participate in Pronatec-MDIC. These results show that turnover is greater when considering turnover not related to job creation or destruction (churning). This suggests that trained workers become more productive after the course and can replace more non-trained workers, leading to higher productivity gains in the short run. Results also suggest that firms that apply but do not have trained workers do not go through this adjustment and see their turnover unchanged.

Resumo

Esta pesquisa explora pela primeira vez o impacto de um programa de treinamento por demanda sobre rotatividade em nível de trabalhador e firma. Lançado em 2014 pelo Ministério de Desenvolvimento, Indústria e Comércio (MDIC), Pronatec-MDIC permite às firmas demandar cursos e nominar trabalhadores. Estimadores de diferença-em-diferença encontram que a duração de emprego dos trabalhadores que se formam dos cursos demandados pelos seus empregadores aumenta por 6 meses. A rotatividade dentro das firmas demandantes varia quando consideramos diferentes grupos de trabalhadores que participam ou não no Pronatec-MDIC. Os resultados mostram que rotatividade é maior quando consideramos rotatividade não relacionada a criação e destruição de emprego. Isso sugere que trabalhadores treinados viram mais produtivos depois do curso e podem substituir mais trabalhadores não treinados, criando ganhos na produtividade no curto prazo. Os resultados também sugerem que as firmas que aplicam, mas que não tem trabalhadores treinados, não passam por esse ajuste e não observam diferenças em suas rotatividades.

Keywords: Education and Training, Turnover, Human Capital.
Palavras chaves: Educação e Qualificação, Rotatividade, Capital Humano
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I. Introduction:

Two of the most marked features of the labor market in Brazil are its high job turnover and stagnant labor productivity. Recent evidence shows that 49.5% of formal workers switched jobs in 2013 (Corseuil et al., 2018b) and that labor productivity has been slowly growing at 1.1% per year in the past decade (IPEA, 2015). While there is widespread theoretical recognition that skill enhancement within a firm affects turnover and labor productivity (Arrow, 1962; Becker, 1993; ILO, 2010; BID, 2015), the literature is limited, to the best of our knowledge, to the impact on labor turnover at worker level (Corseuil et al., 2018a).

The launch of the Programa Nacional de Ensino Técnico (Pronatec) in 2011, the supply-driven training program of Brazil where participants choose the courses they wish to pursue, raised expectations on the coverage of technical education. Theory suggests that as workers get trained and stay longer, they accumulate experience, absorb firm-level knowledge, and become more productive (Arrow, 1962; Becker, 1993). While no evaluations have assessed this hypothesis, aggregated data available for the period after the introduction of the Pronatec shows that the turnover rate from 2011 to 2013 dropped slightly from 53.7 % to 49.5% (Corseuil et al., 2018b), but labor productivity decreased 0.6 p.p. from 2008-2010 to 2011-2013 (IPEA, 2015).

This paper tries to assess how skill enhancement and turnover are correlated at both worker and firm level. We do so by assessing the impact of the demand-driven training version of Pronatec launched in 2014 by the Ministry of Development, Industry and Trade (MDIC in Portuguese). The Pronatec-MDIC version allows firms to demand courses some of their workers take.

This study employs propensity score matching (PSM) and difference-in-differences estimations to compare firms and workers that demand and participate in the training program to those with similar characteristics who do not. To do so, we match administrative data of applications of firms and workers for the 2014-2016 period to a longitudinal employer-employee database for the 2012-2017 period[5]. The result is a comprehensive database that enables us to track employment and firm dynamics before and after program application.

Initial evaluations of both supply- and demand-driven Pronatec are inconclusive. Barbosa et al. (2016) compares workers dismissed in 2011 who complete the short-duration training (FIC) courses between 2011 - 2013 with those who register but do not receive a confirmation. The researchers find that workers who complete the supply-driven training do not present higher employment probability or returns than those who do not get an application confirmation.

Conversely, Almeida et al. (2015) argues that the impact of training varies by provider, course type and economic activity. The study employs PSM techniques to compare students who complete various modalities of technical education with students who follow a general education track. They find that students in courses privately managed and working in the manufacturing sector earn higher wages than those who follow the general education track.
The launch of the demand-driven version of Pronatec in 2014 further promoted the debate. Recent evidence of the program suggests that allowing employers to signal course demands increases the probability of employment but do not induce wage gains considerably (O'Connel et al., 2017). It also confirms that employment effects are more effective in skill-intensive

[5] Relação Anual de Informações Sociais (RAIS), from the Brazilian Ministry of Labor (MTE).

occupations like manufacturing. Despite these initial efforts to evaluate Pronatec, none of the studies explores the turnover of workers.

Corseuil et al. (2018a) assess the impact of training on labor turnover but using the apprenticeship law. Launched in 2000, the law provides tax breaks to firms that offer 2-year contracts to young individuals age 14 to 24 while promoting in-class and on-the-job training. They exploit a change in 2005 in the maximum age requirements (from 17 to 24) to evaluate the impact on labor turnover. Using regression discontinuity, they find a reduction in the turnover of workers who find their first job in large firms. However, they do not explore the effect on firms and their analysis is restricted to young workers with no prior experience.

We instead look at labor turnover at worker and firm level to understand how turnover may differ for workers, whether enrolled or not, and within firms, whether they apply to the program or not. Our analysis is not immune to identification limitations. Individuals who apply to the program might participate for reasons other than class cancellation or oversubscription, arguably uncorrelated to their personal characteristics. The comparison of the characteristics of these groups points to this direction. Additionally, at firm level, a protocol to select firms whose course demands are approved does not seem to exist. Firms more likely to be selected are, on average, large and may have an incentive to secure workers they invest in. To minimize such limitations, we apply PSM to workers and firms and control for time and unit effects.

The paper is structured as follows. In the first two sessions we cover the regional and local literature on the impact of skill enhancement on labor market outcomes, with a special focus on labor turnover. In the third session we briefly describe the statistics of firms and workers that apply to the program. In the fourth session we delved into the methodology and present the results in the fifth one. Finally, we conclude and provide policy implications for Pronatec and technical course design in Brazil.

II. Background of training programs

A. Training in the region

The main conclusion arising from the literature is that supply-driven training programs yield heterogeneous results (Card et al., 2010). In 1986, the U.S. Department of Labor created the largest randomized evaluation of a supply-driven training, the Job Training Partnership Act (Doolittle et al., 1993). This study spearheaded efforts to generate a credible estimate of what would happen to beneficiaries receiving training in the absence of it. Its focus was to assess the impact of training on two common labor market outcomes: employment and wages. In this case, having access to the training increased the percentage of women employed by 2.1 p.p. and that of men by 2.8 p.p. 18 months after the program finished. It also rose the 18-month wages of adult women by 7.2 percent, but not that of adult men (Bloom et al., 1993).

In Latin America, randomized evaluations of hybrid programs have taken place in Colombia, the Dominican Republic, Uruguay and Argentina. In Colombia, Attanasio et al. (2011) found that participating in *Jóvenes en Acción*, a 3-month vocational training combined with a 3-month apprenticeship, increases the probability of formal employment and higher wages in the short term. A subsequent study shows that unemployed poor female workers aged 18 to 25 earn sustained higher wages 10 years after the intervention. Program participation of men has similar effects on employment but induces none on wages (Attanasio et al., 2015).

In the Dominican Republic, benefiting from *Juventud y Empleo*, technical and vocational courses followed by an internship, led to positive impact on wages but not on employment one year after (Card et al., 2011). More recently, the program documents widening employability gap between beneficiaries and non-beneficiaries 6 years after graduating from the program but did not find effects on overall employment (Ibarrarán et al., 2015). Moreover, male students obtain an 8 p.p. increase in employment but no wage gains, while women saw no impact in neither.

In line with these mixed results, a medium-term RCT of *Entra21*, a program in Cordoba, Argentina which combines technical and life-skills training with internships, estimates employment increases of 8 p.p. with wages being 40 percent higher than the control group 1.5 years after the program (Alzúa et al., 2015). However, the effects remain stable for men but dissipate for women 3 years later. A study in Uruguay also estimates that participating in *Yo Estudio y Trabajo*, a 1-year apprenticeship program in public enterprises, increases the probability of finding a job 2 years after the program, but only for a specific age cohort (Araya and Rivero, 2016). Students ages 18 or 19 who did not hold a formal job before were 9 p.p. more likely to find employment.

In synthesis, supply-driven training programs combined with internships/apprenticeships may yield positive employment effects. These effects seem to be mixed and vary by gender in the short run while showing sustained impacts in the long run. Heterogeneous impacts may be the results of program design. Some programs use training vouchers, which makes it difficult for students to find training providers. Others complement training with work, turning difficult for students to find a firm willing to offer a contract or balance the workload demand (J-PAL, 2017).

B. Training in Brazil

Initial evaluations of supply-driven training focused on measuring the impact on employment and wages. Evaluations of the National Plan of Professional Training (Planfor) and Education of Youth and Adults (EJA) assessed the impact of supply-driven training on employment and earnings (Musse and Machado, 2013; Firpo, Fogel, and Jales, 2014). Other researchers assessed labor market outcomes such as the probability of (un)employment and its duration (Paes de Barros et al., 2011; Neri, 2012) and potential earnings (Fernandes, Menezes-Filho e Zylberstajn, 2000).

More recently, with the launch of Pronatec, also a supply-driven training program, some evaluations have shed light on how the program affects labor reinsertion. Barbosa-Filho et al. (2015) uses probit regression to estimate the reinsertion probability of workers who were unemployed in 2011 and graduate from short-term (FIC) Pronatec courses. It finds that access to training does not affect positively the employment probability of students who complete training vis-à-vis those who register but do not receive enrollment confirmation.

Unlike supply-driven training, demand-driven training adjusts to the needs of trainees. It allows beneficiaries to select the training they wish to pursue and even select providers that better suites them. The few evaluations which have explored the effect of demand-driven training in Brazil, have also assessed employment probability and earnings. O'Connel et al. (2017) exploits the program design of Pronatec-MDIC, which leaves out for administrative reasons workers who register for training. Employing a difference-in-differences instrumental variable strategy, the study finds that participating increases the probability of employment by 2 to 3 percent points in the year after program completion without affecting earnings.

That said, the literature on the impact of demand-driven training on labor turnover is limited to Corseuil et al. (2018a). The authors exploit a change in the age eligibility of the Apprenticeship Law[6]. The law states that firms can hire young workers under an apprenticeship contract and indicate which intensive in-classroom courses they should take in exchange of payroll subsidies.

Using partially fuzzy regression discontinuity design (RDD) and adjusted matching method, the authors find that demand-driven training decreases turnover in the short and medium term. After controlling for determinants of program participation, the number of admissions was 16.7% lower than temporary contracts 2-3 years after and 20.6% lower 4-5 years later. Similarly, dismissals decrease by 37.9% after 2-3 years and by 20.9% after 3-5 years.

Evidence of whether Pronatec beneficiaries switch jobs quick is non-existent to the best of our knowledge. This paper thus intends to fill this gap by assessing the impact of Pronatec-MDIC on job turnover.

C. Training models

Models of job turnover claim that turnover does not necessarily generate bad outcomes according to Jovanovic (1979a, 1979b). It can either improve job matching as information about the job and the candidate is revealed in the first months after placement. Or it can worsen the possibility of accumulating human capital unavailable in classrooms such as firm-specific and non-cognitive skills.

On the other hand, models of productivity also assert that the more a worker produces (Arrow, 1962) and the more qualified the worker is (Becker, 1962), the more experience it obtains and the more efficient it becomes at producing its tasks. Both theories suggest that productivity is a function of learning over time. Firms with higher levels of turnover may compromise the learning accumulation of their workers and their productivity as a consequence. The reason may be that high turnover is associated with low levels of commitment and training, from both the workers' and firms' side.

Stylized facts suggest turnover is high in Brazil compared to international standards (Corseuil et. al., 2002; Gonzaga, 2003). Corseuil et al. (2014) finds that turnover[7] is especially high for young workers compared to their adult peers. High youth turnover is concentrated in younger workers (ages 18 - 24) with low schooling (up to lower secondary school) who earn low wages, which makes them easily substitutable.

We also know that youth turnover is not explained by the proportion of young workers entering short-term contracts but by dismissals associated with replacement for other young workers. On one hand, the percentage of young workers hired through temporary contracts did not reach more than 16% between 1996 and 2010 compared to 43% in European countries (O'Higgins, 2012). Although this phenomenon may be changing. On the other hand, 68.6% of the turnover rate[8] in 2014 stems from separations due to firm decisions. In fact, the proportion of young

[6] From 2000-2005 only individuals 14 to 17 years of age were eligible to the program. From 2005 onward, individuals 14 to 24 years old became eligible.

[7] Measured as the difference between hirings and separations in a given year divided by the number of workers active at the end of the year.

[8] Measured as the smallest amount between admitted and dismissed workers divided by the number of workers active at the end of a given year under the regime of the consolidation of the labor laws (CLT by its initials in Portuguese). The rates exclude those dismissals

workers' separations due to substitutions for workers of the same age group was 65% in 2010, and it has grown 12 percent points since 1996 (Corseuil et al., 2013).

These facts may imply that, if firms invest in their employees, they may have fewer incentives to dismiss them and replace them for other workers, allowing them to stay longer. However, the opposite can be true. A recent paper by Rasul et al. (2017) demonstrates that demand-driven vocational training for youth induces higher rates of job-to-job offers, leading to greater worker turnover. The certifiability and transferability of the skills accumulated lead to matches with high productivity firms. Therefore, whether investing in training of workers diminish turnover is an empirical question that we try to answer in this quasi-experimental study that focuses on the job tenure of all workers and labor turnover of firms.

III. Data and descriptive statistics

We use administrative data of Pronatec-MDIC course applications for the years 2014-2016. We use this information to retrieve course application, acceptance and rejection proportions as well as dropout and graduation rates. We then match the data with employment records of firms using the Annual Report of Social Information (RAIS in Portuguese) for 2011-2017. The matched data allow us to obtain the employment status and characteristics of workers (enrolled in Pronatec-MDIC or not) who are employed by the firms that demand the Pronatec-MDIC course.

The first part of the data is from Pronatec-MDIC. Pronatec was established in 2011 to promote the inclusion of vulnerable groups in vocational and technical education. The MDIC version of Pronatec was then launched in 2014 to align course supply to the demand of firms in the manufacturing, trade, and service industries. As summarized in **annex I**, the program protocol involves several steps, from the moment firms and students apply for the program separately to the moment students graduate from the courses.

Firms submit course demands and report their tax ID, the course ID, the municipality where the course takes place, the number of people the companies wish to train, and in some cases, the occupations they demand this course for. As observed in **table 1**, 5,618 firms demand courses between 2014 and 2016. Around 4,300 firms submit applications in at least one year; 1,000 in two years; and less than 200 in at least 3 years.

Table [1]: Times firms demanded courses (2014-2016)

	Freq.	Percent	Cum.
Demanded once	4,335	77.16	77.16
Demanded twice	1,091	19.42	96.58
Demanded thrice	192	3.42	100
Total	5,618		

Source: Calculations of authors using administrative data from Pronatec-MDIC

The Ministry of Development, Industry and Trade filters course demands based on relevance and necessity. Demands for English courses or with high numbers of vacancies are rejected. About half of the demands are filtered out in this stage (O'Connel et al., 2017). MDIC then submits the demands to the Ministry of Education (MEC) which compiles the demands from other ministries and approves them based on budget and complementarity. Similar course demands from ministries, for example, are aggregated and approved. As summarized in **table**

that occur for reasons related to death, retirement, job transition and upon the worker's request as a means to approximate turnover related to decisions of firms.

2, 25.26% firms that submit a demand get an approval and 20.52% of the vacancies demanded are accepted.

Table [2]: Demands and approvals of Pronatec MDIC courses (2014-2016)			
	Demands	Approvals	% approved
Firms	5,618	1,419	25.26
Courses	41,248	6,226	15.09
Vacancies	1,050,169	215,527	20.52
Source: Calculations of authors using administrative data from Pronatec-MDIC			

Once all courses are approved, MEC opens course registration and subsequent enrollment for students. **Table 3** shows that between 2014 and 2016, 55,762 students register at least once for the program, but only 76.69% receive enrollment confirmation in their first attempt. Of those who receive an enrollment confirmation, 64.45% graduate and 25.37% drop out. Of those who do not receive a confirmation, 12.58% were not admitted for administrative reasons (class cancellation and oversubscription) as observed in **table 4**.

Table [3]: Students who register at least once for Pronatec-MDIC courses (2014 - 2016)			
variable	mean	sd	N
registered students			55762
enroll	0.7669022	0.4228078	42764
graduate	0.6545926	0.4755065	27993
dropout	0.2537415	0.4351565	10851
Source: Calculations of authors using administrative data from Pronatec-MDIC			

Table [4]: Reasons for not receiving an enrollment confirmation (2014 - 2016)			
student status	Freq.	Percent	Cum.
no show	5,783	74.6	74.6
transfer	1	0.01	74.61
unfulfilled requirements	993	12.81	87.42
administrative reasons	975	12.58	100
Total	7,752		
Source: Calculations of authors using administrative data from Pronatec-MDIC			

The Pronatec-MDIC dataset is complemented by the RAIS 2011-2017. The RAIS is an annual administrative dataset that contains data on employment and earnings of all the formally-employed workers of formally-registered firms. The RAIS includes detailed information on the employer and the employee (including their tax IDs), and their work relationship (wage, tenure, type of employment, hiring and dismissal date, and reason for dismissal).

In the RAIS, we were able to match the information of 84.16% of firms that make a course request at least once between 2014-2016 and 65.75% of students that which apply to the program at least once between the same timeframe. Unmatched student data in the RAIS could occur because the student was not formally employed within the 2011-2017 period. Combining both datasets allows us to trace the employment history of students before and after program registration, enrollment and graduation, including their turnover rates.

Unlike O'Connel et al. (2017), we manage to match the class that the firm demands to the class the student is registered in using a unique class ID for 2015-2016. From the pool of students registered in these course, we filtered their first applications and whether they are employed by the demanding firm and enrolled at the time the course starts. We also filtered out those who had two simultaneous jobs.

Table 5 shows that of the 17,514 registered for firm-requested courses, 7,531 are employed at course onset. Of those employed, 5,824 are working for the firm that requested the course. And of those employed in the requesting firm, 3,497 are also enrolled in the requested courses. Out of those enrolled, 2,478 graduate and of those not enrolled, 55 were rejected due to administrative reasons. Finally, those working for requesting firms and enrolled in the requested courses stay, on average, employed for 22.62 months from the moment the course starts. On the other hand, those employed by the requesting firm but who did not get the course for administrative reasons remain employed for 13 months from course onset.

Table [5]: Employment history of students registered in MDIC-requested courses (2015-2016)			
variable	mean	sd	N
registered students			17,514
employed at course onset	0.434	0.496	7,607
employed by demanding firm at course onset	0.333	0.471	5,824
employed by demanding firm at course onset and enrolled	0.200	0.400	3,498
employed by demanding firm at course onset, enrolled and graduate	0.141	0.349	2,478
employed by demanding firm at course onset but not enrolled for admin reasons	0.003	0.056	55
employment duration if employed by firm and graduate	22.62	8.727	3,498
employment duration if employed by firm but not enrolled for admin reasons	13.47	7.642	55
Source: Calculations of authors using administrative data from Pronatec-MDIC			

IV. Methodology

We wish to measure the impact of firm application and nomination for course enrollment on job tenure and labor turnover. To do so, we split the methodology at employee and firm level.

A. Worker level

In the case of employees, we wish to measure the impact that being nominated by the firm to participate and graduate from a firm-demanded course has on job tenure. Ideally, we would use administrative constraints as an exogenous source of variation for understanding the impact of the program on employees. That is, use as counterfactual the employees that apply to courses demanded by the firms, but who are denied access for reasons unrelated to their characteristics.

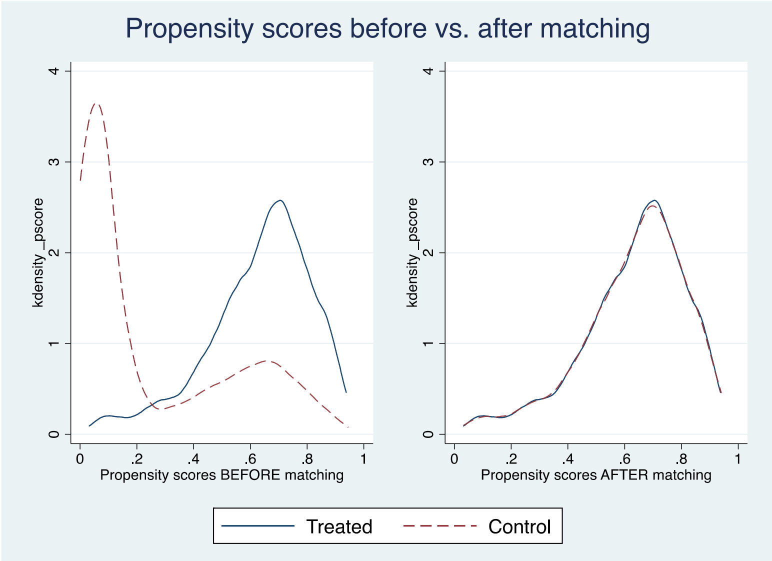
However, there is no nomination protocol and the characteristics of employees rejected for administrative reasons are not similar to that of the treatment group, in part because there are few employees that fulfill these conditions (**table 6**). To construct a credible comparison group of workers with similar characteristics to minimize a potential self-selection issue, the study uses Propensity Score Matching (PSM) (Heckman et al., 1997).

Table [6]: Descriptive statistics of control and treatment groups (2015-2016) before propensity score matching				
variable	treatment	control	t-stat	p-value
age	30.72	32.75	1.53	0.13
sex				
female	0.09	0.05	-1.04	0.30
male	0.91	0.95	1.04	0.30
race				
non-white	0.59	0.91	8.08	0.00
white	0.38	0.09	-7.24	0.00
region				
north	0.08	0.00	-17.95	0.00
north-east	0.30	0.07	-6.24	0.00
south-east	0.25	0.84	11.60	0.00
south	0.16	0.00	-25.49	0.00

center-west	0.21	0.09	-3.10	0.00
education				
low-skilled	0.17	0.38	3.24	0.00
semi-skilled	0.80	0.58	-3.18	0.00
high-skilled	0.04	0.04	-0.02	0.98
occupation				
technicians	0.07	0.00	-15.83	0.00
clerks	0.05	0.02	-1.61	0.11
service and sales workers	0.03	0.04	0.26	0.80
agricultural and fishery	0.08	0.20	2.12	0.04
craft and related workers	0.38	0.65	4.24	0.00
plant and machine operators	0.15	0.04	-4.20	0.00
elementary occupations	0.23	0.05	-5.62	0.00
economic activity				
agricultural	0.02	0.80	14.24	0.00
industry	0.93	0.20	-13.39	0.00
commerce	0.02	0.00	-7.33	0.00
construction	0.01	0.00	-4.48	0.00
service	0.01	0.00	-5.59	0.00
labor market				
job tenure before	38.18	36.13	-0.60	0.55
log mean wage	7.50	7.60	1.81	0.08
course registration				
number of registrations	1.33	1.25	-0.75	0.45
number of enrollments	1.21	0.11	-19.46	0.00
N	3,497	55		
Source: Calculations of authors using administrative data from Pronatec-MDIC				

We match the probability of program enrollment of workers employed by demanding firms while enrolled in courses in 2015-16 with that of workers employed by demanding firms with similar characteristics who do not participate in the program. The matching is built on a logit model that captures the likelihood that an employee is assigned to treatment, based on its pre-treatment characteristics such as age, gender, race, location, education level, job tenure, annual average wage, number of registrations, and enrollment attempts. The match produces treatment and comparison groups that share similar characteristics **(annex II.A.)**. Both control and treatment groups are then assigned to strata according to its propensity score and the Kernel regression estimator chooses the weights so that the closest observations receive greater weight **(figure 1).**

Figure 1. Propensity scores of treatment and control workers before and after PSM



Source: Calculations of authors using administrative data from Pronatec-MDIC

We then follow the job tenure of workers until 2017. To estimate job tenure, we calculate the duration of employment from the moment the course finishes to the moment of the dismissal or last day of 2017. To estimate the difference in job tenure for workers who enroll or graduate and those who do not, we estimate the following specification:

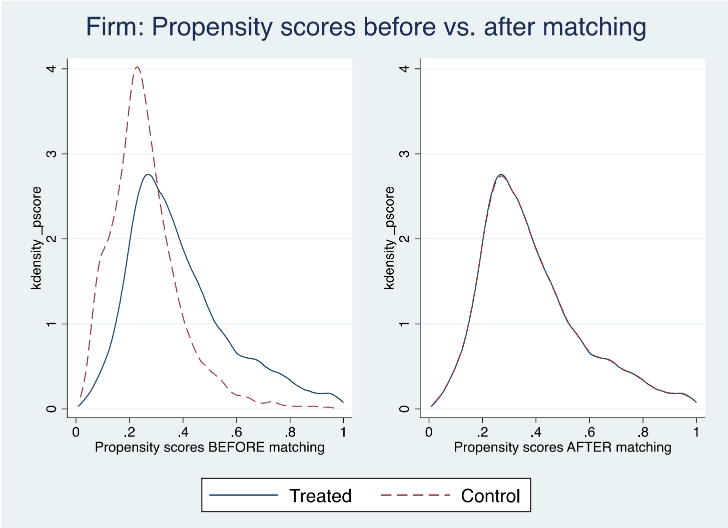
$$y_i = \alpha + \beta \cdot pronatec_{ij} + \gamma \cdot post_t + \delta \cdot pronatec_{ij}{}^{*}post_{it} + \theta \cdot X_{it} + \varphi_i + u_{it}$$

Where $y_{i,t}$is employment duration after the course starts; $pronatec_{ij}$ are year-month dummies indicating whether the worker enrolls into, or graduate from, the program; and $post_t$ accounts for the follow-up period. In other words, each control and treatment unit have one observation before and one after the course. We hypothesize that while enrollment may have a capital accumulation effect on job tenure, graduation may have a further signaling effect. Finally, we control for age, sex, race, location, educational level, occupation, the firm's industry, job tenure before and number of registrations (X_{it}) and cluster the error at state level φ_i. We are interested on the δ coefficient, which indicates the causal impact of participating in Pronatec on job tenure.

B. Firm level

In the case of firms, we wish to measure the impact that firm application has on turnover. To compensate for the lack of an application protocol, we create a comparison group of firms. We do that by using PSM. We match the probability of course approval of firms that obtain training for their workers with that of firms that do not but have similar characteristics. The matching is built on a logit model that captures the likelihood that firm is assigned to treatment based on its pre-treatment features such the as age, gender, race, job tenure, wage and registration and enrollment attempts of workers, and the location, economic activity and size of the firm. To maximize the quality of the match, we identify treatment and comparison groups that have similar characteristics **(annex II.B.)** and use a Kernel regression **(figure 2).**

Figure 2. Propensity scores of treatment and control firms before and after PSM



Source: Calculations of authors using administrative data from Pronatec-MDIC

We then follow the labor turnover of firms from 2011 until 2017, for which we calculate two different rates for each establishment *i* at the end of year *t*:

$$R_{1it} = \left(\frac{H_{it}+S_{it}}{AE_{it}}\right)$$

$$R_{2it} = \left(\frac{H_{it}+S_{it}}{AE_{it}}\right) - abs\left|\left(\frac{H_{it}-S_{it}}{AE_{it}}\right)\right|$$

Where;

H_{it} = admissions in firm i at time t

S_{it} = separations in firm i at time t

$AE_{it} = \frac{(E_{iet}+E_{iet-1})}{2}$; is the average number of workers between two consecutive periods in establishment *i* at time *t*

R_{1it} = is the job flow or the rate at which workers enter and leave a firm *i* at the end of time *t* (Corseuil et al., 2013)

R_{2it} = is the churning rate or the rate at which workers enter and leave a firm not because job creation or destruction (Corseuil et al., 2013)

In other words, while the two job turnover rates consider the flow of admissions and/or separations over the average stock of workers between two consecutive years, R_{1it} focuses on the overall flow of workers while R_{2it} takes on the flow not caused by job creation/destruction. To estimate the difference in job tenure of firms which experience the treatment and those not exposed to it, we estimate the following regression:

$$y_i = \alpha + \beta \cdot Pronatec_i + \gamma \cdot post_t + \delta \cdot Pronatec^{*}post_{it} + \theta \cdot X_{it} + \varphi_i + \sigma_t + u_{it}$$

Where $y_{i,t}$ is job turnover after the first application to the program; $Pronatec_i$ is a year-month dummy indicating whether the firm participates in the program and $post_t$ accounts for the follow-up period. In other words, each control and treatment unit have one observation before and one after the course. Finally, φ_i *and* σ_t are a full set of firm and time effects that accounts for the potential impact that covariate and idiosyncratic shocks may have on job turnover.

We then control for the average age, sex, race, educational level, occupation, job tenure, wage and registration rate of the workers within the firm as well as the location, economic activity and size of the firm. We also control for the number of attempts a worker makes to pursue a course as a proxy for will to thrive which is unobservable. We are interested on the δ coefficient, which indicates the causal impact of participating in Pronatec on job turnover.

V. Results

A. Worker level

Enrollment

We find evidence that workers who enroll stay on average 7 months longer than workers of the same firm who do not enroll in a training course. The result (**table 7**) is significant at 95%.

Table [7a]: Results of job tenure before and after course (without controls)						
job tenure after	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
enrollment	1.296	1.268	1.020	0.307	-1.190	3.782
post	-27.663	1.967	-14.060	0.000	-31.519	-23.807
Pronatec*post (δ)	7.089***	1.780	3.980	0.000	3.601	10.577
_cons	36.878	1.483	24.870	0.000	33.972	39.784
Table [7b]: Results of job tenure before and after course (with controls)						
job tenure after	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
enrollment	0.2219	0.60674	0.37	0.720	-0.967277	1.4111
post	-27.66	1.968999	-14.05	0.000	-31.5219	-23.804
Pronatec*post (δ)	7.0888***	1.780973	3.98	0.000	3.59813	10.5794
_cons	17.875	1.442787	12.39	0.000	15.04728	20.7029
Observations	7,480					
Source: Calculations of authors using administrative data from Pronatec-MDIC						

Graduation

Similarly, we find evidence that workers who graduate stay on average 6.3 months longer than workers of the same firm who do not graduate. These results are consistent with the human capital (Becker 1962, 1993) and job market signaling (Spence, 1973) models. On one hand, the 7 months differential between enrolled and non-enrolled workers suggests that investing in training that is applied on the job enhances capital accumulation and induces experience. That is, doing the course makes workers accumulate skills, become more productive and thus stay longer as they gain experience.

Table [8a]: Results of job tenure before and after course (without controls)						
job tenure after	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
graduation	3.134	1.344	2.330	0.020	0.499	5.768
post	-27.663	1.967	-14.060	0.000	-31.519	-23.807
Pronatec*post (δ)	6.333***	1.904	3.330	0.001	2.602	10.065
_cons	36.878	1.483	24.870	0.000	33.972	39.784
Table [8b]: Results of job tenure before and after course (with controls)						
job tenure after	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
graduation	1.098042	0.6612454	1.66	0.097	-0.1979754	2.394059
post	-27.66274	1.96928	-14.05	0.000	-31.52245	-23.80302
Pronatec*post (δ)	6.333442***	1.905497	3.32	0.001	2.598736	10.06815
_cons	17.43648	1.57236	11.09	0.000	14.35471	20.51825
Observations	6,460					
Source: Calculations of authors using administrative data from Pronatec-MDIC						

Furthermore, graduating from the course can also send a signal to the employer beyond capital accumulation. Finalizing the course can indicate the employer that the worker has diligently completed the course requirements, acquired the most amount of competences possible and thus inducing an extra 6.3 months of job tenure compared to non-enrolled peers.

B. Firm level

At firm level, we find mixed results. The findings are presented for two types of job turnover rates (job flow and churning) and groups (all workers, Pronatec applicants and non-applicants). In general terms, we find evidence that having courses approved increases the labor turnover of firms when using data for all workers and Pronatec applicants.

More specifically, overall labor turnover (R1) for treated firms increases by 0.046 and 0.23 when accounted for all workers and Pronatec applicants, respectively (**table 9**). That is, for every 20 workers employed within two consecutive periods after the intervention, 1 and 5 workers are either hired or dismissed. In the same line, having course approved increases the labor turnover rate not associated with job creation and destruction (R2) by 0.025 and 0.226 points for firms when considering all workers and Pronatec-applicants, respectively (**table 9**). When considering workers who do not apply, turnover decreases but the effect is not significant. We show the results of the minimum turnover (R3) in **annex III.**

Turnover rate 1: $R_{1it} = \left(\frac{H_{it}+S_{it}}{AE_{it}}\right)$ | **Turnover rate 2:** $R_{2it} = \left(\frac{H_{it}+S_{it}}{AE_{it}}\right) - abs\left|\left(\frac{H_{it}-S_{it}}{AE_{it}}\right)\right|$

Table [9]: Results of job turnover (R1 and R2) before and after course demand				
	Without controls		**With controls**	
variable	R1	R2	R1	R2
All workers				
did_post	0.046*	0.048*	0.0462**	0.025**
Observations: 3,788	(0.09)	(0.06)	(0.048)	(0.03)
Pronatec applicants				
did_post	0.228***	0.225***	0.230***	0.226***
Observations: 2,329	(0.00)	(0.00)	(0.00)	(0.00)
Non-applicants				
did_post	-0.023	-0.013	-0.015	-0.007
Observations: 4,308	(0.607)	(0.767)	(0.729)	(0.879)
Source: Calculations of authors using administrative data from Pronatec-MDIC **** significant at 1%; ** significant at 5%; *significant at 10%; standard errors in ()*				

The adjustment in turnover is not immediate and decreases over time. In the first year after the course demand, the labor turnover of trained and non-trained workers does not change. Then the second year, when the adjustment occurs, turnover increases more for trainees (0.090 (R1) and 0.137 (R2)) than non-trainees (0.063 (R1) and 0.058 (R2)). However, with time, the turnover decreases in the third year more substantially for trainees (-0.203 (R1) and -0.263 (R2)) than non-trainees (-0.034 (R1) and -0.051 (R2)). Put differently, qualified workers switch jobs more in the non-immediate short run than non-trainees but revert the process more in the medium run.

Table [11]: Results of job turnover (R1 and R2) before and after course demand					
Trained workers			**Workers who did not apply**		
R1					
T1-T0	T2-T1	T3-T2	T1-T0	T2-T1	T3-T2
0.044	0.090	(-) 0.203	0.018	0.063*	-0.034

R2					
T1-T0	T2-T1	T3-T2	T1-T0	T2-T1	T3-T2
0.0618	0.137**	(-) 0.263***	0.034	0.058*	-0.051
Source: Calculations of authors using administrative data from Pronatec-MDIC *** significant at 1%; ** significant at 5%; *significant at 10%;*					

The greater turnover for trained workers in the second year might be associated with more productive workers leaving firms increasing productivity in the hiring firms. The reduction in turnover for trained workers in the third year might be associated with a firm retaining more qualified workers. If these findings were hold true, we would expect to observe the turnover effect to dissipate completely over time as firms adjust to normal after taking advantage of the productivity gain, a hypothesis we would be able to test with a longer timeframe.

VI. Conclusion and policy implications

The labor market in Brazil has been characterized for high labor turnover and stagnant worker productivity. The launch of Pronatec in 2011, a supply-driven training program where participants choose the courses they wish to pursue, raised expectations on whether capital accumulation could diminish labor turnover and increase productivity. The launch of a demand-driven version of Pronatec in 2014 by the Ministry of Development, Industry and Trade, where firms could demand courses some of their workers could take, further the debate.

This paper explores for the first time the impact of a demand-driven training program on labor turnover at both worker and firm level. It finds that while job tenure of workers that enroll and graduate from courses that their employers demand increases by 7 and 6 months respectively, the labor turnover of demanding firms increases between 0.20 and 0.05 points. That is, for every 20 workers hired in two consecutive periods after the intervention, between 1 and 4 workers are admitted or separated. These results seem to dissipate overtime.

These findings may suggest that turnover is in fact induced by qualification as opposed to job creation or destruction and that participating larger firms make stronger adjustments. These firms may nominate their best workers to the courses, making them more qualified and capable of performing the job of one or more non-trained workers, leading to higher productivity gains and worker substitution. The adjustment is not immediate though and may converge overtime. Turnover only increases the second year after the course demand but decreases a year later, suggesting that it takes time for the effect of training to kick in and reverts with time.

The policy implications of these results are that large scale training programs in Brazil need reform as workers may be trapped in a vicious cycle in which high turnover disincentivizes education and training even when offered for free. Thus, when training demanded by their employees results in higher job duration within that firm, workers can be more motivated to invest and break this vicious cycle. The fact that only one Ministry employs this demand-driven design out of 21 eligible Ministries provides an opportunity to switch to a demand-driven training model to improve labor turnover in the long run[9], a phenomenon that may be holding back the labor productivity potential of firms in the country. Also, this supply-driven programs spent BRL 2.4 billion annually in 2015[10] while demand-driven programs can be more cost-effective.

[9] It is paramount to understand that some supply-driven programs have social objectivities where this statement may not apply like re-insertion of former convicts, insured workers, among others.

[10] Calculated using the federal budget line 20RW

References

Aguas, M. (2012). Ensino Profissional e Rendimentos do Trabalho: uma análise para o Brasil. Nota Técnica do IPEA.

Almeida, R., Anazawa, L., Menezes, N., and Vasconcellos, L. (2015). Investing in Technical and Vocational Training: Does it Yield Large Economic Returns in Brazil? Policy Research Working Paper No. 7246. Education Global Practice Group. Washington, D.C.: WB.

Alzúa, M. L., Cruces, G., and Lopez, C. (2015). Youth Training Programs Beyond Employment: Experimental Evidence from Argentina. Working Paper No. 177. CEDLAS, Universidad Nacional de La Plata, Argentina.

Araya, Federico and José Ignacio Rivero. (2016). Impact of a work-study programme for teenagers: evidence from a randomized controlled trial.

Arrow, Kenneth. (1962). The economic implications of learning by doing. Review of Economic Studies, 1962, vol. 29, issue 3, 155-173.

Attanasio, O., Guarín, A., Medina, C., and Meghir, C. (2015). Long Term Impacts of Vouchers for Vocational Training: Experimental Evidence for Colombia. NBER Working Paper 21390. Cambridge, MA.: National Bureau of Economic Research.

Attanasio, O., Kugler, A., & Meghir, C. (2011). Subsidizing Vocational Training for Disadvantaged Youth in Colombia: Evidence from a Randomized Trial. American Economic Journal: Applied Economics, 3(3), 188-220.

Barbosa, F., Porto, R., e Liberato, D. (2016). Pronatec Bolsa-Formação: Uma avaliação Inicial sobre Reinserção no Mercado de Trabalho Formal. Brasília, D.F.: Ministério da Fazenda.

Becker, Gary. (1962). Investment in human capital: a theoretical analysis. Journal of Political Economy. Volume 70, Number 5, Part 2. Chicago, IL.: The University of Chicago Press.

Becker, Gary. (1993). Human Capital: a Theoretical and Empirical Analysis, with Special Reference to Education. Third edition, Chicago, IL.: The University of Chicago.

Bloom, H., Orr, L., Cave, G., Bell, S., and Doolittle, F. (1993). The National JTPA Study: Title II-A Impacts on Earnings and Employment at 18 months. Abt Associates Inc. Research and Evaluation Report Series 93-C. Washington, D.C.: U.S. Department of Labor.

Blundell, R. and Dias, M. C. (2009). Alternative approaches to evaluation in empirical microeconomics. Journal of Human Resources, 44(3):565–640.

Calero, C., Gonzalez, V., S., Y.S.D., Kluve, J., & Corseuil, C. (2016). Can Arts-Based Interventions Enhance Labor Market Outcomes Among Youth? Evidence from A Randomized Trial in Rio De Janeiro. Journal of Labour Economics.

Card, D., Ibarraran, P., Regalia, F., Rosas-Shady, D., & Soares, Y. (2011). The Labor Market Impacts of Youth Training in the Dominican Republic. Journal of Labor Economics, 29(2), 267-300.

Card, D., Kluve, J., and Weber, A. (2010). Active Labour Market Policy Evaluations: A Meta-analysis. The Economic Journal 120, F452-F477.

Corseuil, C. H., Foguel, M., & Gonzaga, G. (2018a). Apprenticeship as a stepping stone to better jobs: Evidence from Brazilian matched employer-employee data. Department of Economics, Pontifícia Universidad Católica do Rio de Janeiro (PUC-Rio), Brazil.

Corseuil, C. H., Foguel, M., Gonzaga, G., & Ribeiro, E. P. (2013). Youth Labor Market in Brazil Through the Lens of the Flow Approach. Proceedings of the 41st Brazilian Economics Meeting from the Brazilian Association of Graduate Programs in Economics.

Corseuil, C. H., Foguel, M., Gonzaga, G., & Ribeiro, E. P. (2014). Youth Turnover in Brazil: Job and Worker Flows and an Evaluation of a Youth-Targeted Training Program. Working Paper No. 0155. CEDLAS, Universidad Nacional de La Plata, Argentina.

Corseuil, C.H., Pero, V., e Da Rocha, Leandro. (2018b). Turnover, Learning by Doing, and the Dynamics of Productivity in Brazil. Discussion Paper No. 231. Brasília, Brasil: IPEA

Corseuil, C.H., Pontual, E., Santos, D., & Dias, R. (2002). Criação, Destruição e Realocação de Empregos no Brasil. Rio de Janeiro, Brasil: IPEA

Departamento Intersindical de Estatística e Estudos Socioeconómicos (DIEESE). (2016). Rotatividade no mercado de trabalho brasileiro: 2002 a 2015. Deparatamento Intersindical de Estatística e Estudos Socioeconômicos. São Paulo, SP: DIESEE.

Doolittle, F., Bell, S., Bloom, H., Cave, G., Kemple, J., Orr, L., Traeger, L., and Wallace, J. (1993). The Design and Implementation of the National JTPA Study: A Summary. New York, NY: Manpower Demonstration Research Corporation.

Fernandes, R., Menezes-Filho, N. A., e Zylberstajn, H. (2000). Avaliando o PLANFOR: O programa do Sindicato dos Metalúrgicos de São Paulo. Texto para Discussão IPE/USP

Firpo, S., Fogel, M. e Jales, H. (2014). Evaluating the Impact of Stratified Randomized Experiments with an Application to a Brazilian Public Training Program. Working paper.

Gonzaga, Gustavo. (2003). Labor turnover and labor legislation in Brazil. Texto para discussão No. 475. Economia, v. 4, n. 1, p. 165- 222, 2003.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. The Review of Economic Studies, 64(4):605–654.

Ibarrarán, P., Kluve, J., Ripani, L., and Rosas, D. (2015). Experimental Evidence on the Long-Term Impacts of a Youth Training Program. Discussion Paper No. 9136. Bonn, Switzerland: Institute of the Study of Labor (IZA).

Idem. (1979b). Firm-specific Capital and Turnover. The Journal of Political Economy, Volume 87, Issue 6 (Dec., 1979, pp. 1246-1260. Chicago, IL.: The university of Chicago Press.

Instituto de Pesquisa Econômica Aplicada (IPEA). (2015). Produtividade No Brasil: Desempenho e Determinantes. Volume 1, Desempenho. Brasília, D.F: IPEA. ISBN: 978-85-7811-228-8.

Jovanovic, Boyan. (1979a). Job Matching and the Theory of Turnover. The Journal of Political Economy, Volume 87, Issue 5, part 1, 972-990. Chicago, IL.: The university of Chicago Press.

Kaplan, D., Novella, R., Rucci, G., and Vazquez, C. (2015). Training Vouchers and Labor Market Outcomes in Chiel. IDB Working Paper Series NO. IDB-WP-585. Washington, D.C.: IADB.

Musse, I. e Machado, A.F. (2013). Perfil dos indivíduos que cursam educação profissional no Brasil. Economia e Sociedade, Campinas, v. 22, n. 1 (47), p. 237–262, abr. 2013.

Neri, M. (2010). A Educação Profissional e Você no Mercado de Trabalho. Rio de Janeiro: FGV/CPS.

O'Connel, Stephen, Mation, L., Bevilaqua, J. and Dutz, M. (2017). Can business input improve the effectiveness of worker training? Evidence form Brazil's Pronatec-MDIC. Policy Research Working Paper 8155. Washington, D.C.: WB.

O'Higgins, Niall. (2012). This time it's different? Youth labor markets during 'The Great' Recession. IZA Discussion Paper n. 6434.

OECD (2016). Perspectivas Económicas De América Latina 2017. Perspectivas Económicas De América Latina, OECD, 10, 2016. doi:10.1787/leo-2017-es.

Paes de Barros, R, Carvalho, M., Franco, S. e Vieira, A. (2011). Avaliação da pertinência do programa do programa Bolsa Qualificação para o combate à pobreza no Espírito Santo, Texto para discussão do IPEA N.1583.

Portela, A., Ripani, L., Lima, L., Amorim, V., Arabage, A., Camargo, J., and Soares, S. (2016). A stocktake of vocational education and training cycle in Brazi: From school entry to labor market transition. Washington, D.C.: IADB.

Rasul, I., Alngosi, L., Bandiera, O., Bassi, V., Burgess, R., Sulaiman, M., and Vitali, A. (2017). Tackling Youth Unemployment: Evidence from a Labor Market Experiment in Uganda. Economic Organisation and Public Policy Discussion Papers No. 64. London, UK: LSE.

Reis, M. (2015). Vocational Training and Labor Market Outcomes in Brazil. B.E. Journal of Economic Analysis and Policy, 15, 377-405.

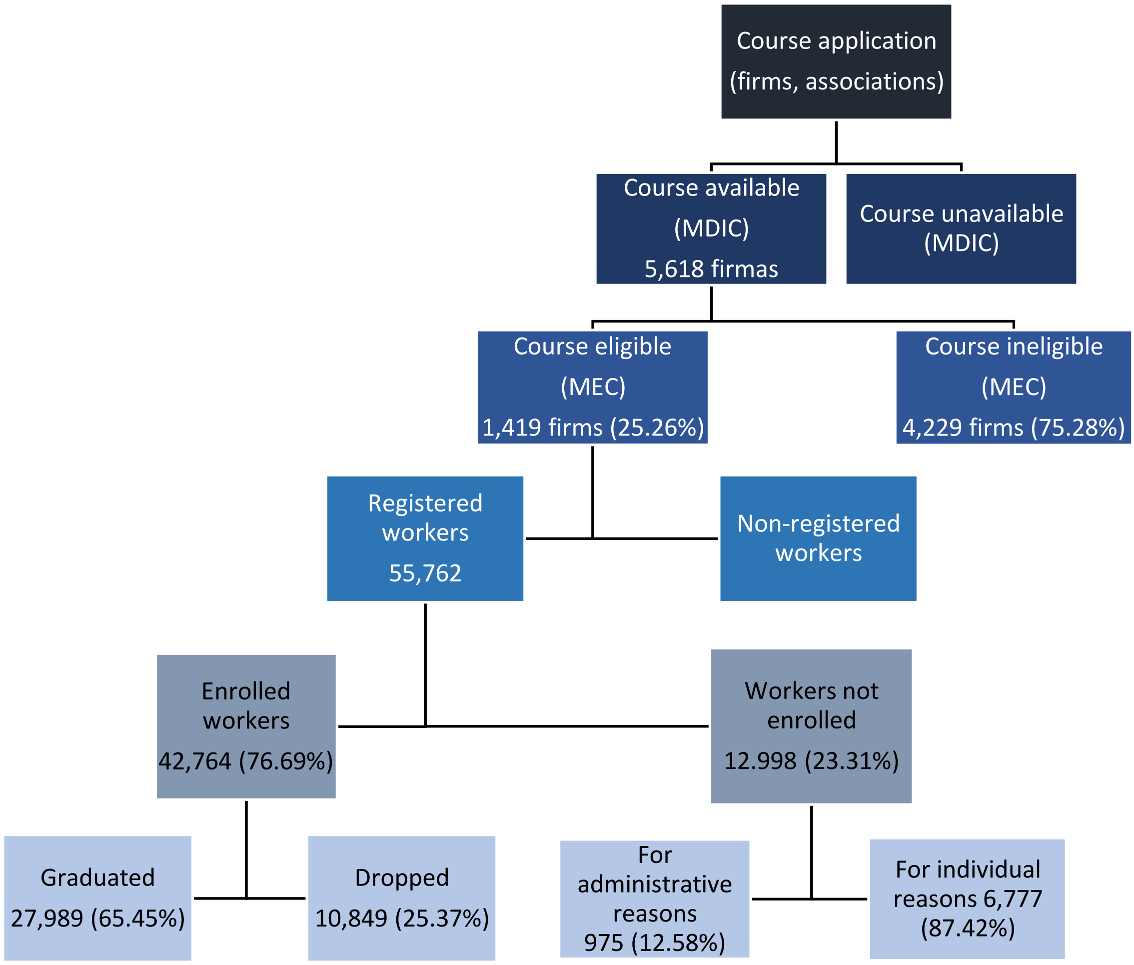
Severnini, E. e Orellano, V. (2010). Efeito do ensino profissionalizante sobre a probabilidade de inserção no mercado de trabalho e sobre a renda no período pré-Planfor. V.11, n.1, jan/abr 2010, Economia. Brasília, DF.

Silva, Joana, Rita Almeida, and Victoria Strokova. (2015). Sustaining Employment and Wage Gains in Brazil: A Skills and Jobs Agenda. Directions in Development No. 99182. Human Development. Washington, D.C.: WB.

Spence, Michael. (1973). Job Market Signaling. The Quarterly Journal of Economics, Vol. 87, No. 3. (Aug., 1973), pp. 355-374.

Annex

I. Overview of course request process



Source: Built from O'Connel et al., 2017 using authors' own calculations

II. Propensity Score Matching

A. Worker level:

Table [A1]: Descriptive statistics of control and treatment groups after PSM Workers employed by requesting firm at course onset (2015-2016)							
	Mean				t-test		
variable	treatment	control	%bias	%reduct |bias|	t-stat	p-value	V (T) / V (C)
age	30.724	31.08	-4.4	67.8	-1.85	0.065	0.99
male	0.9133	0.89557	5.4	77.6	2.52	0.012	.
non-white	0.58569	0.59142	-1.2	91.4	-0.49	0.627	.
north	0.08412	0.04492	11.8	56	6.69	0	.
north-east	0.29843	0.30072	-0.5	91.6	-0.21	0.835	.
south-east	0.24635	0.22117	5.8	-11.1	2.49	0.013	.
south	0.1568	0.15422	0.8	96.8	0.3	0.766	.
center-west	0.21431	0.27897	-15.8	-1187.8	-6.29	0	.
illiterate	0.00114	0.00286	-6.5	-92.1	-1.61	0.108	.
MS incomplete	0.16567	0.18655	-5.8	18.5	-2.29	0.022	.
MS complete	0.08698	0.10386	-6.1	-100.1	-2.4	0.016	.
HS incomplete	0.14077	0.14421	-1	75.6	-0.41	0.681	.
HS complete	0.56881	0.52876	8.1	-53.1	3.37	0.001	.
college incomplete	0.0206	0.01717	2.2	57.1	1.05	0.292	.
college complete	0.01602	0.0166	-0.4	96.1	-0.19	0.85	.
senior officials and managers	0.00401	0.00229	2.9	-130.9	1.28	0.2	.
professionals	0.0103	0.01001	0.3	89.6	0.12	0.905	.
technicians	0.06695	0.0681	-0.4	96.2	-0.19	0.849	.
clerks	0.04807	0.05608	-3.3	72.3	-1.51	0.132	.
service and sales workers	0.02976	0.02546	2.4	47.2	1.09	0.274	.
agricultural_fishery	0.08412	0.0907	-2.3	14.8	-0.97	0.33	.
craft and related workers	0.37825	0.36967	1.8	69.6	0.74	0.458	.
plant and machine operators	0.14564	0.16824	-6.6	-21.1	-2.6	0.009	.
elementary occupations	0.2329	0.20944	6	72.9	2.36	0.018	.
cnae21	0.02403	0.02289	0.7	91.4	0.32	0.752	.
cnae22	0.03977	0.0495	-4.5	54.1	-1.97	0.049	.
cnae23	0.89156	0.88355	2.2	90.9	1.06	0.289	.
cnae24	0.00029	0.00086	-1.6	71	-1	0.317	.
cnae25	0.01516	0.00801	6.2	-129.3	2.8	0.005	.
cnae26	0.01516	0.02146	-3.7	79	-1.96	0.05	.
cnae27	0.00629	0.0083	-2	70.3	-0.98	0.325	.
cnae28	0.00143	0.002	-0.7	94.3	-0.58	0.563	.
cnae29	0.00629	0.00343	2.9	61.9	1.72	0.086	.
job tenure before	38.174	37.118	4.7	18.5	2.21	0.027	1
log mean wage	7.5017	7.4959	1.2	96.2	0.48	0.632	0.66*
number of registrations	1.329	1.4129	-12.5	-3959.1	-4.9	0	0.77*
month course started	667.64	667.13	8.9	93.8	5.01	0	0.75*
N	3,495	3,985					
Source: Calculations of authors using administrative data from Pronatec-MDIC							

B. Firm level:

Table [A2]: Descriptive statistics of control and treatment groups by firm (2014-2016)							
	Mean			%reduct |bias|	t-test		V (T) / V (C)
variable	treatment	control	%bias		t-stat	p-value	
age	32.844	33.122	-5.2	30.6	-3.2	0.001	0.82*
male	0.71704	0.70956	2.3	91	1.47	0.143	0.89*
non_white	0.46256	0.44414	4.8	70.1	2.92	0.004	0.95*
disabled	0.00389	0.00421	-1	37	-0.63	0.531	0.40*
professionals	0.00972	0.01111	-1.9	-7.1	-1.12	0.264	0.87*
technicians	0.01952	0.02043	-1	83.6	-0.54	0.586	0.98
clerks	0.08472	0.08685	-1.4	83.7	-0.81	0.417	0.79*
service_sales_workers	0.14864	0.14991	-0.5	97	-0.34	0.732	0.90*
agricultural_fishery	0.06482	0.06583	-0.5	98.2	-0.35	0.729	0.90*

craft_related_workers	0.04363	0.043	0.6	98.1	0.26	0.799	0.79*
plant_machine_operators	0.45572	0.43996	4.3	-20.5	2.67	0.008	0.94*
elementary_occupations	0.10365	0.10697	-1.6	82.1	-0.92	0.357	0.85*
north	0.09362	0.09178	0.6	85.3	0.38	0.706	.
north_east	0.20912	0.20361	1.4	89.5	0.81	0.418	.
south_east	0.36557	0.36854	-0.6	93.2	-0.37	0.714	.
south	0.20955	0.21788	-1.9	87.8	-1.21	0.227	.
center_west	0.12214	0.11819	1.2	75	0.72	0.469	.
agro	0.01461	0.0211	-5.8	-57.4	-2.94	0.003	0.71*
industry	0.72091	0.70927	2.5	84	1.54	0.125	0.98
commerce	0.10595	0.10753	-0.5	89.1	-0.31	0.76	0.99
construction	0.05124	0.05192	-0.2	99.1	-0.18	0.855	0.99
service	0.05887	0.06316	-1.7	77.8	-1.07	0.285	0.94*
others	0.04842	0.04702	0.7	75.2	0.39	0.695	1.03
MS_incomplete	0.10558	0.10197	1.9	76.4	1.13	0.259	0.82*
MS_complete	0.08333	0.08118	1.3	87.8	0.87	0.383	0.86*
HS_incomplete	0.12189	0.11734	2.4	79.6	1.65	0.099	0.84*
HS_complete	0.60347	0.6142	-3.4	44	-2.13	0.033	0.90*
college_incomplete	0.03931	0.03835	0.8	85.2	0.55	0.585	1.04
college_complete	0.045	0.04534	-0.3	97.1	-0.15	0.884	0.94*
enrollment_rate	1.0868	0.99832	4.7	-353.6	2.78	0.006	6.21*
total_employment	37.413	37.192	0.4	99.1	0.16	0.877	0.87*
job_tenure_workers	2.8679	3.0264	-7.1	72.2	-3.65	0	0.63*
log_wage_m	7.3727	7.3931	-4.9	87.9	-2.66	0.008	0.80*

Source: Calculations of authors using administrative data from Pronatec-MDIC

III. Minimum labor turnover results

Turnover rate 3: $R_{3it} = min\left|\left(\frac{H_{it}|S_{it}}{AE_{it}}\right)\right|$

R_{3it} = is the minimum job flow or the minimum rate at which workers either enter or leave a firm *i* at the end of time *t* (DIESSE, 2016)

Table [A3]: Results of job turnover (R3) before and after course demand

variable	Without controls	With controls
All workers		
did_post	0.024*	0.027**
observations	3,788	
Pronatec applicants		
did_post	0.112***	0.113***
observations	2,329	
Non-applicants		
did_post	-0.006	-0.003
observations	4,308	